Band-specific features improve Finger Flexion Prediction from ECoG

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***Abstract*—ECoG-based BCIs attract intensive attention recently. ECoG can provide a higher spatial resolution and signal quality compare to EEG recordings. These characteristics make possible to localize the source of neural signals precisely with respect to certain brain activities such that ECoG-based BCIs may realize a complex and apt neuroprosthesis. Signal processing is a very important task in the BCIs research for translating the brain signals into commands for a computer application or a neuroprosthesis. Here, we present a linear regression method based on the amplitude modulation of band-specific ECoG including tap delay for individual finger flexion prediction. We especially study the influence of the frequency band decomposition on the prediction. An efficient feature selection can reduce the number of features by a factor greater than 10 without a strong impact on the prediction. According to the experimental results, the gamma band (60-100Hz) seems the carry more useful information than the others. This method won the BCI competition IV dedicated to this mapping.**

I. Introduction

The goal of brain-computer interface (BCI) research is to reinstall a control and communication capability for those with severe motor disabilities by translating brain signals into commands for a computer application or a neuroprosthesis [1].

The neural electrophysiological signals currently being studied in the BCI domain ranges from electroencephalogram (EEG), electrocorticogram (ECoG), to local field potential (LFP) and single unit activity/multiunit activity (SUA/MUA). These different types of brain signals have their own characteristics and there is still controversy on the type of signals which is most suitable for the BCI applications. Nevertheless, considering ECoG whose electrodes are placed over the surface of the cortex, it provides a higher spatial resolution and signal quality than the classical scalp EEG recordings. On the other hand, ECoG is less invasive than those intracortical recordings like LFP, SUA/MUA which by far are only studied in animal experimental BCI systems. By recognizing the merit of ECoG recordings, several groups of BCI researchers have carried out tests on the efficiency of using ECoG as control signals for human BCIs [2], [3], [4], [5].

Initially, ECoG electrodes arrays were implanted beneath the dura mater (i.e., under the skull but over the surface of the cortex) for severe epileptic patients in order to identify the sources generating epileptic seizures for presurgical planning. Typically, the diameter of one ECoG electrode is of 4 mm with 1 cm inter-electrode distance. Therefore ECoG can provide a spatial resolution of approximately 1 cm [6].

Spatial resolution plays an important role in BCI [3]. The fine spatial resolution of ECoG provides a better opportunity for directly decoding brain activities. Therefore, it is possible to implement direct neural interfaces which are difficult to be accomplished through EEG-based BCIs.

To study the usability of ECoG in BCIs, several research groups had recorded ECoG signals from the participants when they performed certain kind of tasks related to the brain functional areas where the implanted electrode arrays had covered. The tasks include center-out reaching or pointing task [3], single finger flexion [2] and cursor trajectory [5].

For the application of finger flexion prediction from ECoG, we noticed that a simple linear regression model of amplitude modulation of band-specific ECoG signals was efficient [3]. In this paper, we made contribution to this method in two ways: first, improve the stability of the model by replacing the inverse operation in the solution of the linear model by pseudo-inverse operation; second, propose to use a stepwise feature selection procedure to select the relevant frequency bands and electrodes. To prove the efficiency of this method, it was applied to the ECoG data set from BCI competition IV, which is dedicated to the task of finger flexion prediction. Results showed that this method achieved the highest value of correlation coefficient between the predicted and true finger flexion recordings.

II. BCI Competition IV - Data Set 4

The task of the data set 4 in BCI competition IV is to predict the finger flexion from ECoG recordings, which is accessible through [7]. Detail description about this data set is found in [8], [2]. Here, we only provide a brief summary.

This data set contains three subjects who were epileptic patients under surgical planning by implanting a subdural electrode array to identify the epileptic focus for further surgical removal. They were willing to participate recording experiments: while they performed finger flexion task, the corresponding ECoG and finger flexion time courses were recorded simultaneously. The electrode array was in arrangement of an 8*6 or 8*8 grid (n.b., the exact location of the electrodes was unknown to the competitors because the electrode order had been scrambled in the preparation of this data set).

The subjects were instructed to flex one certain finger by the corresponding word displaying on a screen. The execution of finger movement lasted 2 seconds and it was followed by a 2-second resting period. There were 30 movement stimulus for each finger resulting in 600-second recordings for each subject. The first 400-second recordings were used as training purpose and last 200-second recordings as testing purpose. The subjects were instructed to move one individual finger at a time. Off-line analysis of the finger flexion time courses showed that the movements of the last three fingers (i.e., middle, ring and little finger) were correlated in a considerable way.

The ECoG signals were recorded through the general-purpose BCI system BCI2000 [9], bandpass filtered between 0.15 to 200 Hz and sampled at 1000 Hz. The finger movements were recorded using a dataglove sampled at 25 Hz. Figure 1 provides an example of the visualization of the ECoG signals and the corresponding finger movement time course from subject 1. Due to space limitation, only a subset of ECoG electrodes is displayed. The correlation coefficient between the predicted and true finger flexion time course is used as the evaluation criterion for this data set in the competition.

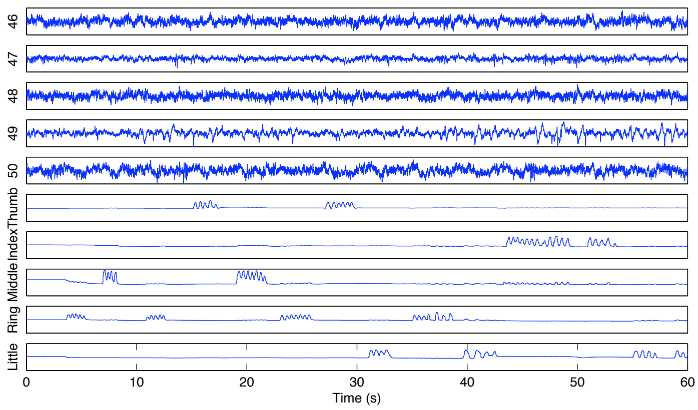

Fig. 1. Example ECoG signals: the first 60 seconds of the training data set from channel 46 to 50 from subject 1. The last 5 rows show the corresponding finger movement time course.

III. Methods

A. Pre-processing

Band decomposition: The evidence of sensorimotor ECoG dynamics has been reported in several specific frequency bands including slow potentials, sub-bands (1-60 Hz), gamma band (60-100 Hz), fast gamma band (100-300 Hz) and ensemble depolarization (300-6k Hz) [3].

Amplitude modulation: Being inspired by the rate coding approach used in spike train decoding, Sanchez proposed a band-specific amplitude modulation (AM) as the descriptor for ECoG signal decoding, which is defined as the sum of the power of the voltage of the band-specific ECoG signals v in a time bin Δt:

$$x(t_n) = \sum_{t=0}^{\Delta t} v^2(t_n + t) \tag{1}$$

where $\Delta t = t_{n+1} - t_n$. We simply let $\Delta t = 40ms$ so the resulting band-specific AM features have the same sampling rate (i.e. 25 Hz) as that of the dataglove position measurements. And the band-specific ECoG signals v were generated through equiripple finite impulse response (FIR) filters by setting their band-pass specifications as the frequency band aforementioned: sub-bands (1-60 Hz), gamma band (60-100 Hz) and fast gamma band (100-200 Hz) (n.b., in order to cater the frequency content available in our studied case, the fast gamma band was defined only up to 200 Hz and the ensemble depolarization frequency band was not taken into account). Therefore for each channel, raw ECoG signals were decomposed into three sets of band-specific ECoG signals. Finally, for each set of band-specific ECoG signals, we applied Equation (1) to estimate the band-specific AM features.

Feature selection: Since the ECoG electrode array covered quite a large zone of cortical area, only a subset of electrodes was correlated to the task. On the other hand, we have no a prior information about which frequency band contributed more than the other. Therefore, for each finger and each subject, we use a stepwise feature selection procedure to identify the optimal AM features (i.e., the combinations of channel and frequency band) from the whole set which equals 186, 142 and 192 AM features respectively for subject 1, 2 and 3. The feature selection procedure was based on the method of train and validation (i.e. 3/5 of training dataset are used for training and 2/5 for validation). The stopping criterion is satisfied when the validation correlation coefficient does not increase or when a user predefined maximum number of cycles is reached.

B. Linear Regressor Model

The relationship between the features and the target signals or the interaction between features is not clear for this case. We simply applied a linear model as a decoder for its robustness property. Although, we noticed that other advanced methods have been used for ECoG signals decoding, for example, the Kalman filter [5]. This method is not suited for our case because the first method needs a finger model which we do not have. The linear model we used here takes the form as follows:

$$d(t_n) = W^T \vec{x}(t_n) \tag{2}$$

where d is the finger position as measured by a data-glove. $\vec{x}(t_n)$ is the tap-delay AM feature vector $\vec{x}(t_n) = [x(t_n)x(t_{n-1})\dots x(t_{n-k})]^T$. k is the number of tap-delays and is optimized with the value of 25 for our case. The coefficients W of the model are trained with the Wiener solution:

$$W = E(\vec{x}^T\vec{x})^{-1}E(\vec{x}^T d) \tag{3}$$

where E is the expected mean. In order to improve the stability for estimating the coefficients of the Wiener model, we replace the inverse operation in Equation (3) by the pseudo-inverse.

IV. Results

First, we present the feature selection results. For the feature selection procedure as described in section III-A, we stop the stepwise selection when the maximum number of cycles is equal to 10 or when the correlation coefficient for the validation set does not increase (as the criteria used to justify the similarity between the predicted and true finger flexion in this competition is correlation coefficient).

Figure 2 gives an example on the evolution of the feature selection procedure for the index finger of subject 1. The Y-axis indicates the correlation coefficients of training, validation and test set respectively, which are plotted as a function of the number of selected features. We found that there is no evident increment with testing correlation coefficient for more than 4 features from this plot.

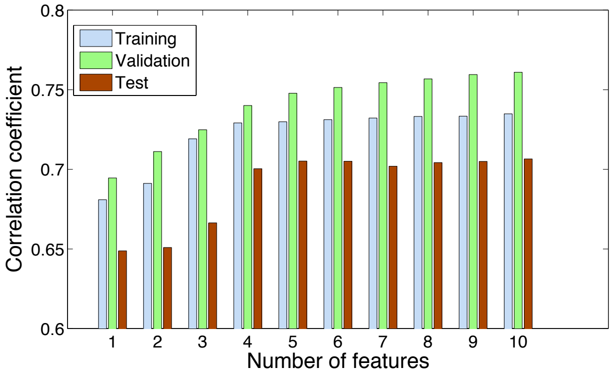

Fig. 2. Evolution of feature selection procedure for the index finger of subject 1: the correlation coefficients are plotted as a function of the number of selected features. For each step, the three bars from left to right represent training, validation and test set respectively.

Figure 3 gives another point of view on the evolution of the feature selection procedure for the same subject and finger. This figure emphasizes the prediction power of each selected feature. Actually, we found that the last 3 features have timid contribution to the task of finger flexion prediction.

Figure 4 shows that the gamma band (60-100Hz) is the most selected band for the 10 best features (1-60Hz: 27%, 60-100Hz: 44% and 100-200Hz: 29%). This is valid independently to the subject and the rank.

Next, we summarize the prediction performance of this method using the testing dataset in terms of correlation coefficient between the predicted and true finger movement in Table I [1]. In order to highlight the effect of frequency-specific decomposition, the results based on raw ECoG are also provided for comparison.

[1]The last element in the table I indicates the correlation coefficient value averaged over all fingers and subjects for the method based on band-specific ECoG, which is slightly different from the result of value 0.46 announced in the competition [10] because finger ring was removed from the evaluation in the competition due to the finger movements of finger ring, by off-line inspection, were quite correlated with those of finger middle and finger little.

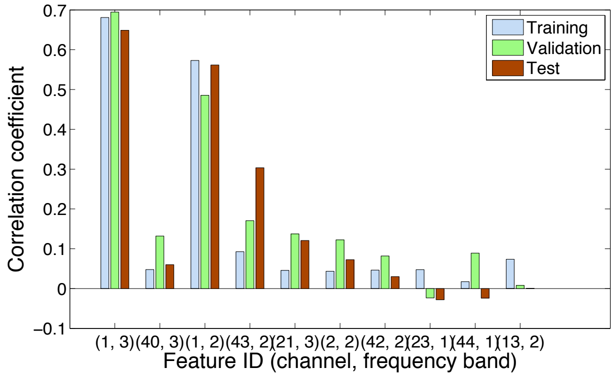

Fig. 3. The X-axis shows, from left to right, the features selected in each step. Each feature is indicated by two elements: channel and frequency band (sub-bands is indicated by 1, gamma band by 2, and fast gamma band by 3). The Y-axis indicates the correlation coefficients of training, validation and test set respectively regarding each feature individually.

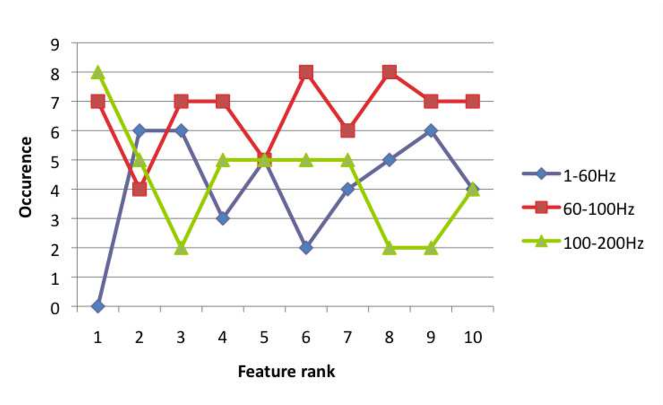

Fig. 4. The X-axis shows the 10 best features ranking. The Y-axis indicates the occurence of each frequency band over 15 cases (3 subjects x 5 fingers) concerning the selected feature.

TABLE I
THE PREDICTION PERFORMANCE OF THE METHODS IS PROVIDED IN TERMS OF CORRELATION COEFFICIENT BETWEEN THE PREDICTED AND TRUE FINGER MOVEMENT FOR EACH FINGER AND SUBJECT. THE LAST COLUMN REPRESENTS THE RESULTS AVERAGED FOR EACH SUBJECT AND EACH METHOD; THE LAST TWO ROWS REPRESENT THE RESULTS AVERAGED FOR EACH FINGER AND EACH METHOD.

Subj.	Method	Thumb	Index	Middle	Ring	Little	Av.
1	Raw ECoG	0.00	0.13	0.01	0.22	0.06	0.08
	Band-specific ECoG	0.58	0.71	0.14	0.53	0.29	0.45
2	Raw ECoG	0.26	0.28	0.19	0.34	0.15	0.25
	Band-specific ECoG	0.51	0.37	0.24	0.47	0.35	0.39
3	Raw ECoG	0.40	0.25	0.31	0.29	0.27	0.31
	Band-specific ECoG	0.69	0.46	0.58	0.58	0.63	0.59
Av.	Raw ECoG	0.22	0.22	0.17	0.28	0.16	0.21
	Band-specific ECoG	0.59	0.51	0.32	0.53	0.42	0.48

From Table I, we observed that the method based on band-specific AM features obtained better performance than the method using raw ECoG signals. It justifies that the decoding power of brain signals lies in certain frequency band and other frequency bands are more likely as background noise.

We also provided an example for the predicted finger movement for subject 3 using the method based on band-specific ECoG AM features in Figure 5. For comparison, the corresponding true finger movement time course is plotted in the same figure.

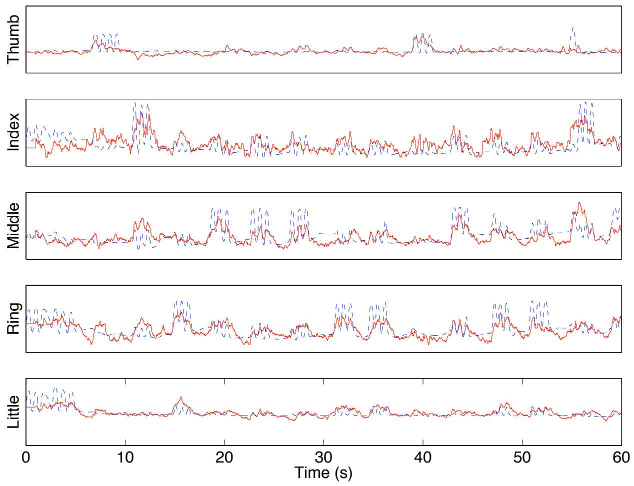

Fig. 5. Predicted (solid red) and real (dash blue) finger flexion time course for the first 60 seconds in testing data set from subject 3.

V. Conclusion and Further Work

This article proposed a linear decoding scheme based on band-specific amplitude modulation for predicting finger flexion from ECoG signals. The high correlation between the predicted and true finger flexion shows that ECoG-based BCIs is promising for implementing a practical and apt neuroprosthesis. In particular, we can infer from the experimental results that the sensitivity profile of ECoG signals is band-specific. While it is not clear if the frequency parcellation scheme used here is optimal or if it is depended on task and subject.

We also noticed that the method failed in predicting in some cases, especially for the middle finger of subject 1. It is partly due to the considerable correlation between middle, ring and little finger. On the other hand, it is possibly due to the method does not take into account the interaction between the features. We tried to introduce some user-defined interaction terms into the linear regression model. It may improve the decoding accuracy using less number of regressors. Thus, non-parameter models incorporating the interaction terms into the decoding model, for example, using multivariate adaptive regression splines (MARS) [11] will be investigated in the future.

In the stepwise feature selection procedure, we found that some features which did not contribute too much to the prediction of finger flexion alone but ranked high in the sequence of the feature selection procedure. This inspires us to consider the correlation between band-specific ECoG signals. It is suggested that incorporating the feature correlation into feature selection, for example, using correlation feature selection (CFS) method [12], may produce an optimal compact feature set.

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